Karlsruhe Institute of Technology

# Online Neural Network-based Language Identification

Master’s Thesis

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# Contents

# Motivation

Karlsruhe Institute of Technology

- ASR and SLT commercially great success ["OK, Google", Siri, Jibbigo]
- Best performing ASR models are still trained on one source language.[1]

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- Performance increase for multilingual tasks[1], UI streamlining.

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# Specific Applications

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Karlsruhe Institute of Technology

## Lecture Translator

- Low latency, online application
- Small source language amount make performance increase likely

## European Parliament

- SLT already employed consistently[2]
- Many languages challenging, great potential.

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# Related Work I

## Historically

- PRLM[a], PPRM[b][3]
- Gaussian Mixture Models (GMM)s [4]

[a] single-language phone recognition followed by language-dependent, interpolated n-gram language modeling

[b] multiple single-language phone recognizers and language-dependent parallel phone recognition

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# Related Work II

## Modern Approaches

- VSM[a] + PPRM[5]
- I-Vector approaches[6][7]

[a] Vector Space Modelling

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# Related Work III/Based on

## Similar Approaches

- Matejka et. al[8] similar setup: BNF $\rightarrow$ LID, with averaging 5 LID nets.
- [9] M. Heck et al. evaluate LID approaches prospect of Lecture Translator integration: PPRM/PRLM + Hybrid.

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# Theory of LID

- Given input $S = \{s(1), s(2), \ldots, s(T)\}$, $\{L_1, L_2, \ldots, L_N\}$

**Formulation of LID Task[11]**

$L^O = \arg\max_l p(S|L_l)$

With segmentation into phones $\upsilon$ (sequence $\Upsilon$):

$L^O = \arg\max_l P(\Upsilon|L_l)$

With Viterbi decoding on set of phone models $M$:

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Combining last 2 equations:

$$\boxed{L^O = \arg\max_l \sum_{\forall\Upsilon} P(S|\Upsilon, M)P(\Upsilon|L_l)}$$

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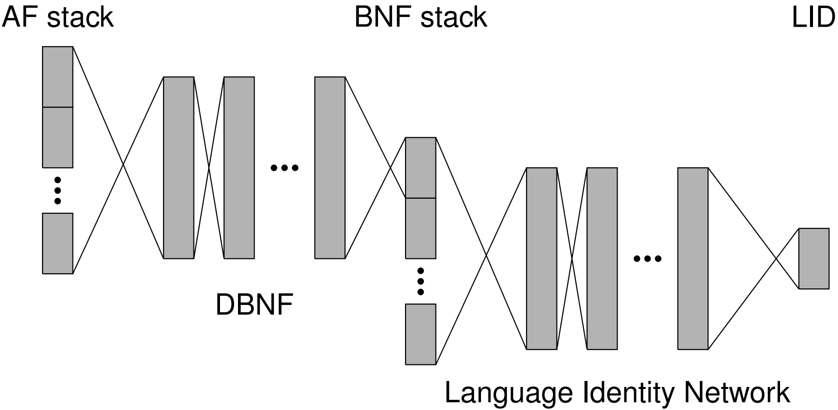
# Experimental Setup



# Data Sets

## Euronews 2014

- 10 Languages (EN, FR, DE, AR, ES, IT, PO, PT, RU, TR)
- Original Corpus: 72h / Language, Reduced corpus: 18h / Language (Random Sampling of 10.000 speakers)
- 80 % train data, 10 % each dev/test set.

## Lecture Data

- 3 Languages (EN, FR, DE) 10h per language.
- KIT lectures, InterACT25, DGA talks
- Evaluation of EUNews results, Proof-of-concept for Lecture Translator integration.

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# Data Sets II

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## European Parliament

- 7 Languages (EN, FR, DE, ES, IT, PO, PT) 3.6h per language
- Simultaneous translation of all EUParliament speeches
- Further Evaluation, Proof-of-concept for EUParl integration.

# Feature Extraction

# DBNF

# DNN Structure

# Demo

# Evaluation Metrics

# Smoothing Filters

# Results

# Future Work

# Questions?

# References I


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